DESIGN AND IMPLEMENTATION OF INTELLIGENT MPPT CONTROLLER FOR HYBRID RENEWABLE ENERGY SOURCES UTILIZED IN IRRIGATION

A SYNOPSIS

Submitted by

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1. INTRODUCTION

The present population of the world is 8.04 billion as of 2023, out of which 17.76 % of the population belongs to India (ranks 1st largest populated country in the world). The world is growing in population tremendously, and the green environment is drastically becoming endangered due to various factors of commercialization. The most important green environment is unnoticeable, and fuels such as coal and petroleum are getting depleted when compared to the requirements. In this technological environment, everyone should rely on renewable energy resources compared to non-renewable ones, which are high-cost, polluting, and non-biodegradable. In this era, renewable resources such as solar energy resources, hydro energy resources, wind energy resources, etc., require the proper channel to implement. Natural resources, such as wind and solar energy, have been considered in this work. Wind energy resources are harvested using wind turbines, whereas solar energy is produced through solar photovoltaic panels. India ranks 4th in the world concerning wind power capacity and 5th among the solar power installed capacities. Recent studies reveal new technologies being introduced to harvest renewable energy resources efficiently. The harvested power is ultimately used for many applications such as home electrification, office or school buildings, farming, and many stand-alone applications. In this work, agricultural-based irrigation application is considered.

The agricultural farming sector is considered for this work's application, which meets humankind's survival by utilizing fewer resources. But for the farming purpose, the challenges which are to be taken into the light are,

1. Effective water resources management
2. Proper irrigation scheduling based on climate changes
3. Crop health monitoring

Considering the water resources for irrigation purposes, about 4 % of the world's freshwater resources have to serve 17.7 % of the world's population (India's population). Also, nearly three-quarters of India's population relies on rural agricultural income. Whereas the agriculture sector alone consumes almost 80 % of groundwater through canals, wells, tanks, etc., On the other hand, another main

challenge farmers face while carrying out farming is the unstable climate conditions. Due to the stochastic variation in climate conditions, such as frequent draughts and heavy rainfalls, the irrigation is improper, and the crops are not healthy and completely damaged. The fields that depend upon rainfall for irrigation remain in a drought without water, leading to heavy losses in farming. Considering the irrigation challenges, the Indian agriculture procedure consumes more water by manually seeing the irrigation requirements and watering system. Also, unexpected rainfall on an irrigated farm further reduces crop health and yields. This leads to the wastage of available water resources and crop yield. The flood-based irrigation practice was carried out in earlier stages, which is still in training. As a result, it is efficient up to the range of 25-40 %. Various controlled irrigation systems have been introduced to address these issues, such as the sprinkler-based irrigation method, which is 60-85 % efficient. Similarly, another way says the drip irrigation method is utilized, which is 80-90 % efficient compared to earlier methods.

The precision agriculture practice considers weather parameters such as wind speed, soil moisture, rainfall status, temperature, humidity, and many more to monitor and irrigate the farm to reduce water consumption and workforce. Nowadays, various research is carried out in smart precision agriculture with the Internet of Things (IoT). It is mainly utilized to monitor the farm environment with the help of sensors connected to the crop field, ensuring the growth and health of the plant by monitoring the nitrogen, phosphorous, and potassium (NPK) levels, as mentioned by Grimblatt et al. [1]. The farmer can control the irrigation process remotely, depending on the observed data. The problem is not solved by only monitoring the farm and controls from a remote location. It is resolved by incorporating various algorithms that decide irrigation scheduling and predicting the weather conditions of the near future, which facilitates the irrigation process.

Ultimately, the combination of renewable energy-based irrigation practices is considered in this work. This work proposes a methodology to efficiently handle renewable energy resources for agricultural monitoring and prediction regarding irrigation. Thus, the green environment is saved with the green energy resources.

2. LITERATURE REVIEW

A stand-alone wind-solar battery system is proposed as part of the planned system. The main goal is to use renewable energy and harvest the maximum power from the energy resources without any spill-off. Various controller topologies are found to harvest the generated power to guarantee maximum energy efficiency. One of the traditional controllers is a perturbed & observed (P & O) algorithm to achieve leading Power Point. This algorithm continuously monitors the output power and compares it with the previous output power to acquire maximum capacity, as mentioned by Sheik Mohammed et al. [2]. Still, it tends to have oscillations around MPP.

Similarly, another MPPT technique is the Incremental Conductance (IC) method, as stated in the article of Rajesh K. et al. [3]. It contains a sequence of inputs, and the incremental output is obtained to achieve the maximum power. Similar to P&O, the modified P&O is available by changing the perturbation size by fixing the threshold value stated by Ahmed & Salam [4]. Various MPPT algorithms include Weed Optimization, Fuzzy Logic Controller (FLC) analyzed by Jemaa et al. [5], Swarm Intelligence (SI), hybrid controllers, Artificial Intelligence networks, Genetical Algorithm (GA) utilized by both Yousaf et al. [6] and Khedr [7], and more upcoming algorithms stated by Yap et al. [8]. Rai et al. [9] and Elobaid et al. [10] found that Artificial Neural Networks suit well for hybrid energy systems. Also, the ANN-based MPPT tracking seems robust but attains faster search even for non-linear systems. Under the roof of ANN, Kumar et al. [11] presented the Radial Basis Function Network (RBFN), which is useful for hybrid systems as it has faster convergence properties when compared with the traditional algorithms in simpler network structures.

The further improvised algorithm was stated by Lin et al. [12], which is a modified Elman neural network. Another example of a hybrid controller is ANFIS, a combination of ANN and FLC algorithms started by Aldair et al. [13] and a few others with neural networks with gain scheduling PI, which was performed by Ulaganathan and Devaraj [14]. Although there are various techniques available for considering maximum power point tracking methodologies, the artificially intelligent power tracking method suits well for all-weather isolations that occur suddenly. Also, it rectifies the limitations that arise in conventional methods, such as the lack of

adaptiveness, robustness, self-learning capabilities, steady-state error, and power oscillations at MPP. The existing systems need manual tuning, increasing the computational tuning and making it difficult to implement in a real-time environment.

Conversely, the research work consists of irrigation at the agricultural farm. The next part of the work is concentrated on human-less irrigation process automation. Though various techniques and schemes are available to automate the system, everything lags in designing and developing a prediction model. The prediction models are widely possible with deep learning algorithms. The various algorithm involved in deep learning includes convolutional neural networks, long short-term memory networks, recurrent neural networks (RNN), generative adversarial networks (GAN), radial basis function network (RBFN), multilayer perceptron (MLP), deep belief network (DBN), self-organizing map (SOM), autoencoders, etc., Because of the mentioned prediction algorithms, many are productive in the field of object prediction and textual prediction. The RBFN and LSTM are better utilized for time-series prediction. LSTM architecture contains blocks, which are recurrent connected units consisting of one or more memory cells to store and access the information for a certain period to improve the performance and with lesser gradient error, as mentioned by Farzad et al. [15]. This LSTM-based network is employed by Yang [16] for many weather monitoring applications for carrying out irrigation works based on the data acquainted from sensors through IoT. Yu et al. [17] collected five years of weather data from New York City from April 2019 to May 2020 and processed the sensor data first, then the weather was predicted from the measured data. In the other case, based on the soil moisture data and temperature data, the weather is expected for irrigation using the DliSA device developed by Kashyap et al. [18].

Similarly, a case study was conducted by Chhetri et al. [19] in Bhutan for monthly prediction over the Simtokha region of Thimphu. Based on the data obtained from the National Center of Hydrology and Meteorology department (NCHM), the monthly rainfall is predicted with Deep bi-directional LSTM with the help of Tensor flow. Based on the review, it is found that bi-directional LSTM works well for the prediction-based irrigation methodology.

3. RESEARCH PROBLEM

The combination of two renewable energy sources considered in this thesis are wind energy and solar energy-based stand-alone energy systems. The problem occurs in the interconnection of energy systems. Wind energy is prevalently available throughout the day either partially or completely. Similarly, solar is available during the daytime. So the DC bus which interconnects both wind energy system and solar energy system along with battery and load deviates by not maintaining the constant voltage. The existing MPPT controllers often struggle to efficiently manage the diverse and intermittent nature of hybrid renewable sources, leading to suboptimal energy harvesting and increased dependency on traditional power sources. This research aims to address this gap by designing and implementing an intelligent MPPT control system that adapts to the dynamic conditions of hybrid renewable energy systems, thereby enhancing the overall energy efficiency and sustainability of agricultural irrigation processes. To mitigate these issues, the controller is meant to develop the controller that gives the duty control for each of the systems individually.

1. Tracking the maximum power from renewable energy sources
   - Finding the duty cycle for wind power for corresponding wind speed

$$D_w = \begin{cases} 1 & if\ P_{w\_meas} = P_{w\_target} \\ 0 & if\ P_{w\_meas} \neq P_{w\_target} \end{cases} \quad (1)$$

   - Finding the duty cycle for solar power for corresponding solar irradiation and temperature

$$D_s = \begin{cases} 1 & if\ P_{s\_meas} = P_{s\_target} \\ 0 & if\ P_{s\_meas} \neq P_{s\_target} \end{cases} \quad (2)$$

2. Battery management system - Finding the duty cycle for battery charging and discharging

$$D_{batt} = \begin{cases} 1 \in charging & if\ 20 \leq soc \geq 80 \\ 0 \in discharging & otherwise \end{cases} \quad (3)$$

3. Load management system

$$D_{load} = \begin{cases} 1 & if\ D_{batt} = 0\ \&\ load = 1 \\ 0 & if\ D_{batt} = 1\ \&\ load = 0 \end{cases} \quad (4)$$

4. Achievement of voltage stability at DC-DC link bus

$$V_{load} + V_{loss} = \sum_{ws=1}^{max} V_w + \sum_{S_{ir\&temp}=0}^{max} V_s + \sum_{SOC=1}^{max} V_{batt} \quad (5)$$

5. Irrigation volume estimation

$$I_{v\_tot} = \frac{1}{N}\sum_{n=1}^{N} I_v(SN_n, t) \tag{6}$$

6. Irrigation time estimation

$$I^a(t) = \frac{1}{SN_n}\sum_{n=1}^{A_n} I_v(SN_n, t) \tag{7}$$

Where D_w is the duty cycle for wind energy source, D_s is the duty cycle for solar energy source, D_{batt} is the duty cycle of battery, P_{w_meas} is the measured wind power, P_{w_target} is the target required for the corresponding measured wind speed, P_{s_meas} is the estimated solar power, P_{s_target} is the target needed for related solar irradiation and temperature, *SOC* is the state of charge of battery, V_{load} is the voltage required at the load, V_{loss} is the voltage loss, *ws* is the wind speed, and $S_{ir\&temp}$ is the solar irradiation and temperature. The SN_n is the slave node of the actuator node A_n at positions 1,2, …N.

4. OBJECTIVES OF THE WORK

The main objectives of this research work are,

1. Performance analysis of Artificial intelligence-based MPPT controller for wind solar hybrid energy system compared to conventional P&O and Fuzzy algorithms in terms of settling time and efficiency.
2. Designing a Hybrid Master Power Controller (HMPC) with a Radial Basis Function Neural Network (RBFNN) Algorithm to analyze its settling time and efficiency.
3. Real-time implementation of Federated deep learning control strategy with wind solar prototype.
4. Implement deep bi-directional long short-term memory (DBLS-TM) technique for data monitoring, ET_0 estimation, weather prediction, and scheduling.

5. PROPOSED METHOD

This thesis contributes towards developing a controller for achieving MPPT, battery management, and load management from stand-alone renewable energy sources for irrigation prediction and estimation.

5.1 Modeling of Artificial Intelligence-based MPPT controller

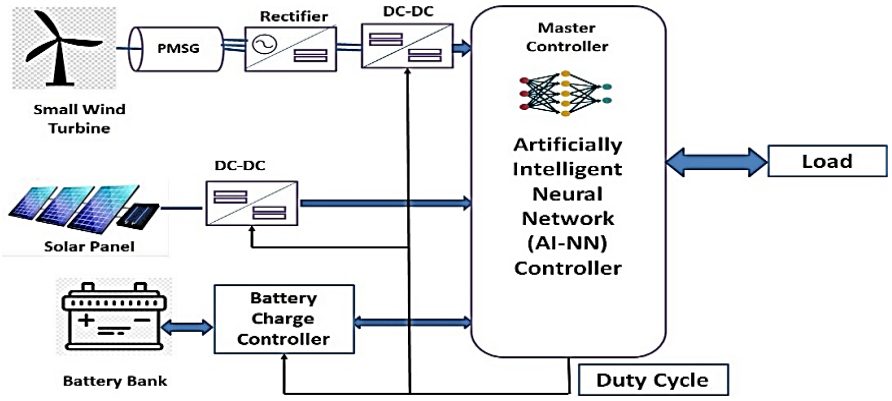


Figure 1: Block diagram for AI-NN controller for hybrid renewables

Neural networks, like the human brain, are made up of connections of neurons that process a machine's or system's learning law. The entire block diagram for AI-NN control is shown in Figure 1. To produce the most reliable and best performance, neural networks train a data set of inputs with a group of targets. To achieve the maximum power, the hybrid wind-solar DC output voltage and output current are fed as inputs for the neural network fitting, and the duty cycle for the boost converter is obtained as the output. The best maximum power is obtained by training the network with any of the classical MPPT algorithms. The current and average voltage is attained with the real-time data of small wind and solar panels under various environmental conditions. The artificially intelligent neural network is trained for multiple real-time wind speed conditions, voltage, current, solar irradiance (G), and temperature profiles. During the training process, the weights were adjusted with the training data to attain the target data. The controller is fit to use only when trained with multiple iterations and minimum error.

5.2 Design and Analysis of Hybrid Master Power Controller (HMPC) using RBF-NN Algorithm

The proposed HMPC is modeled with the RBFNN topology to achieve maximum power and reduce the complex structure. The main reason to choose the RBF-NN algorithm for MPPT is to achieve faster tracking and universal approximation with a Gaussian activation function. Also, it allows the system to be stable under stand-alone working conditions, with wind and solar renewable operations integrated with the

battery. This single controller masters all three procedures of maximum power achievement for the wind and solar energy systems, battery management systems, and load management systems. The following process flow shown in Figure 2 attains the process of achievement of all the tasks.

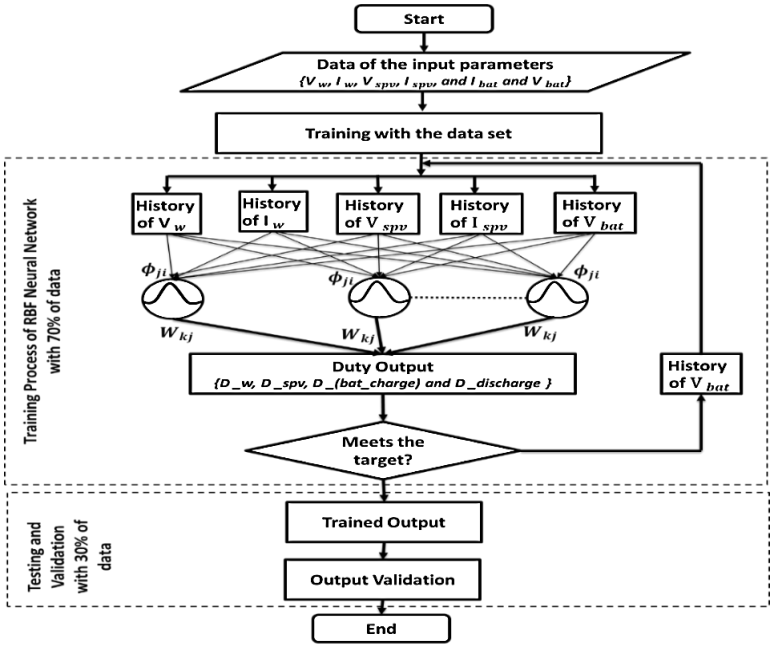

Start
Data of the input parameters
{V w, I w, V spv, I spv and I bat and V bat}
Training with the data set
Training Process of RBF Neural Network with 70% of data
History of V w
History of I w
History of V spv
History of I spv
History of V bat
Duty Output
{D_w, D_spv, D_(bat_charge) and D_discharge }
Meets the target?
Testing and Validation with 30% of data
Trained Output
Output Validation
End

Figure 2: Flow chart of RBF-NN Algorithm

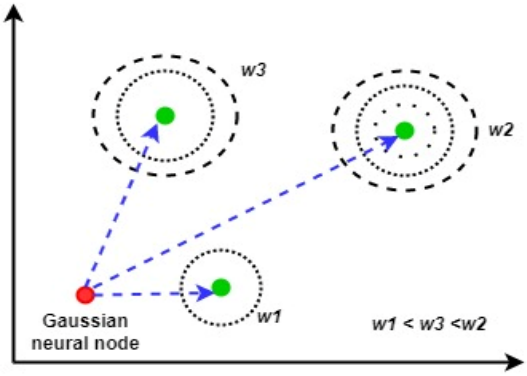


Figure 3: MPPT tracking with RBFNN algorithm

The RBF-NN algorithm works anonymously without manual intervention by assigning the tracking centres by the k-means nearest neighbour clustering method. In the above Figure 3, each point refers to the Gaussian neural nodes, and the circles around them represent the corresponding nodes' range. In this case, it is the power obtained at any instance. The control strategy is operated by attaining its maximum power point depending on its weight and distance from the red end. By that, w_1's weight is lesser when compared with w_3 and w_2, respectively, so the tracking is attained faster.

6.3 Design and implementation of federated deep learning control strategy

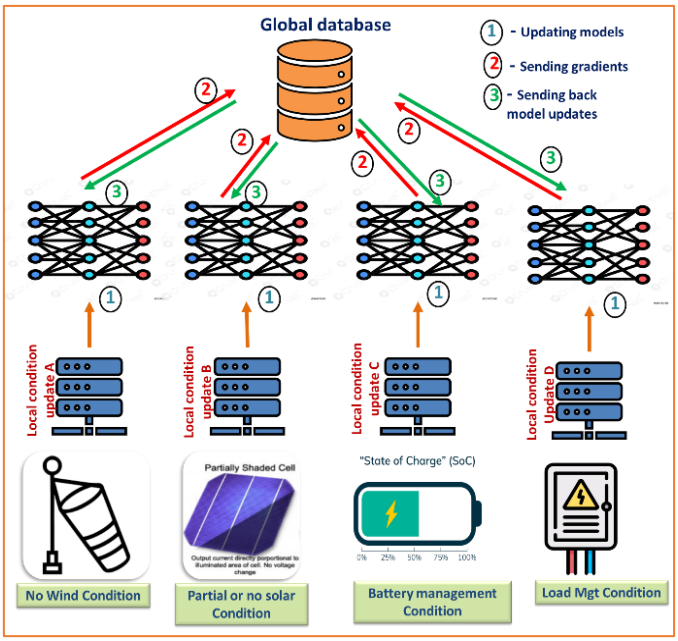


Figure 4: Federated learning control model of the hybrid energy system

Based on Figure 4, the system is deployed with the available data before the system installation. With the available dataset, the system is deployed and carried out with the operation. They then depended upon the operating constraints such as no wind condition, partial shading condition or irradiation condition, battery operating ranges, and load management condition. The system will be operated based on these operating conditions, and the new dataset will be produced. The latest data will be carried out with a local model update with the AI algorithm, and then the gradients will be generated. Finally, it is sent to the global database model for overall updates, which are sent to the local data controllers. The algorithm process flow is shown below in detail.

Algorithm 1: Federated Deep Learning-based MPPT Control Strategy

Assigning the D_{w_mpp}, D_{s_mpp}, D_{batt_mpp} and D_{load_mpp}
Global training process
    Training the controller for 1…N days
    Allow the circuit to be operational
End of global training
For wind turbine operation ($1 \leq t \leq k$), k = no. of days
    Senses the output wind power W_p
    Allows **D_{w_mpp}**
    Records the voltage at DC link $V_{dc\_link\_wind}$
    Local training update on **D_{w_mpp} epoch**
End
For SPV operation ($1 \leq t \leq k$), k = no. of days

13: Senses the output wind power S_p
14: Allows $\mathbf{D_{s\_mpp}}$
15: Records the voltage at DC link $V_{dc\_link\_spv}$
16: Local training update on $\mathbf{D_{s\_mpp}}$ **epoch**
17: **End**
18: **For** Battery operation ($1 \leq t \leq k$), k = no. of days
19: Senses the output wind power B_p
20: Allows $\mathbf{D_{batt\_mpp}}$
21: Records the voltage at DC link $V_{dc\_link\_batt}$ and SOC
22: Local training update on $\mathbf{D_{batt\_mpp}}$ **epoch**
23: **End**
24: **For** Load operation ($1 \leq t \leq k$), k = no. of days
25: Records the voltage at DC link $V_{dc\_link\_load}$
26: Local training update on $\mathbf{D_{load\_mpp}}$ **epoch**
27: **End**
28: **Update the global epoch**
29: **Follow step 3 again**

6.4 Implementation of deep bi-directional long short-term memory (DBLS-TM) technique for Irrigation monitoring and estimation:

The design of the Deep Data Logger and Irrigation Activator Unit (D^2LIAU) uses Deep Bi-directional Long Short-Term Memory, as shown in the Figure 5.

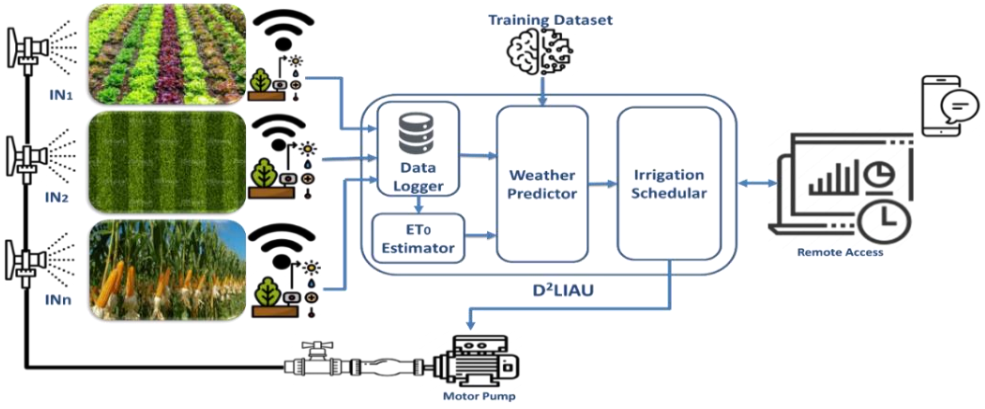


Figure 5: Overall block of the Deep Data Logger and Irrigation Activator Unit (D^2LIAU)

The above Figure reveals that the system consists of three sub-blocks that are essentially required for irrigation. The sub-blocks are classified as (i) Data logging unit, (ii) ET_0 Estimator, (iii) Weather predictor, and (iv) Irrigation scheduling unit. All these four things are essential for carrying out the irrigation process without any manual intervention. Each module is the most critical part of making the task successful and efficient. Initially, the data logger aggregates the sensors deployed for

monitoring purposes. The logged farm's parameter is useful to estimate the Evapotranspiration (ET_0) of the crops to find out the water requirements. Once the ET_0 is calculated, the weather predictor will analyze and predict the soil moisture requirements compared to the trained data set using Deep Bi-directional Long Short-Term Memory. Finally, the predictor allows the scheduler to schedule the irrigation process by intimating the water requirements and duration of how much water is required for irrigation purposes. Simultaneously, the valve connected to the particular crop gets activated as and when needed with the command from the device. The ultimate goal is achieved with the help of the Deep Data Logger and Irrigation Activator Unit (D^2LIAU).

Algorithm 2: Deep Data Logger and Irrigation Activator Unit (D^2LIAU)

Data Logging Unit
Sensing the input parameters from the sensors deployed at each slave node
Sensor nodes are fixed for each crop variety
For each $n = 1,2, \ldots N$
$SN_n = (f_n, t) \in I_f$.
I_f *is the irrigation field*
End for
Aggregate the observed information,
$SN_n \triangleq \{S_{T,n}, S_{H,n}, S_{SM,n}, S_{R,n}, S_{WS,n}\} \in I_f, n = 1,2,\ldots N$.
Accumulate all sensor nodes at the master node and store the information
$MN \triangleq (SN_1, SN_2, SN_3, \ldots SN_n) \in I_f, n = 1, 2,\ldots N$.
Monitor the farm's climate condition through remote access
ET_0 Estimator
Sensing the temperature values for ET_0 estimation
For each n= 1,2, …, N and t = 1,2,3, …. ∞
Estimate
$S_{T\_max}(f_n,t) = mint(S_T(f_n,t))$
$S_{T\_min}(f_n,t) = \max t(S_T(f_n,t))$
Compute
$ET_{0\_n} = ET_0(S_{T\_max}$ *and* $S_{T\_min})$
End for
Weather Prediction Unit
Initializing the sensor nodes
For $(1 \leq t \leq k)$, k= no. of days
Compute field average
$I_{f\_avg} = [I_{f1}+I_{f2}\cdots I_{ft}\ldots I_{fk}]$
Compute standard deviation
$I_{f\_std} = [I_{f1}+I_{f2}\cdots I_{ft}\ldots I_{fk}]$
Fetch the sensor data
$SNn \triangleq \{S_{T,n},S_{H,n},S_{SM,n},S_{R,n},S_{WS,n}\} \in I_f, n = 1,2,\ldots N$
Calculate f_t, i_t, and $\mathfrak{C}_t$
Update the memory state of the cell $\mathbb{C}_t$

34:	**Calculate** output, O_t
35:	**End for**
36:	**Calculate** hidden state h_t
37:	**Calculate** the hidden state for the forward direction $\overrightarrow{h_t}$
38:	**Calculate** the hidden state for the forward direction $\overleftarrow{h_t}$
39:	**Calculate** the predicted output y_{pred}
40:	Store the predicted output in the memory set
41:	**Irrigation Scheduler**
42:	**Update** $S_{SM,n}$ and $S_{SM+1,n}$
43:	**Calculate** irrigation volume I_v
44:	**Estimate** total irrigation requirement I_{v_tot}
45:	**Activate** the corresponding actuator for irrigation I^a
46:	Execute the routine irrigation process

6. OVERVIEW OF THE RESULTS

The Artificial neural network algorithm's output characteristics have been analyzed with MATLAB Simulink environment. To achieve the maximum power point, the system must fit perfectly during training and validation. The regression value for the system under consideration is 0.9999. After the successful training process, the tool provides the Simulink block set of the neural network controller. The toolbox is now trained and fit to act as an MPPT controller for the design. The designed MPPT is compared with P&O and fuzzy-based algorithms. The ANN controller performs well when compared with the conventional algorithm. Though the system worked well with ANN, the system is complex to design and time-consuming during the training process. The Radial Basis Function Neural Network (RBFNN) algorithm was designed and compared with P&O, IC, FLC, ANN & Fuzzy, and FHO algorithms to resolve this issue as shown in Figure 6.

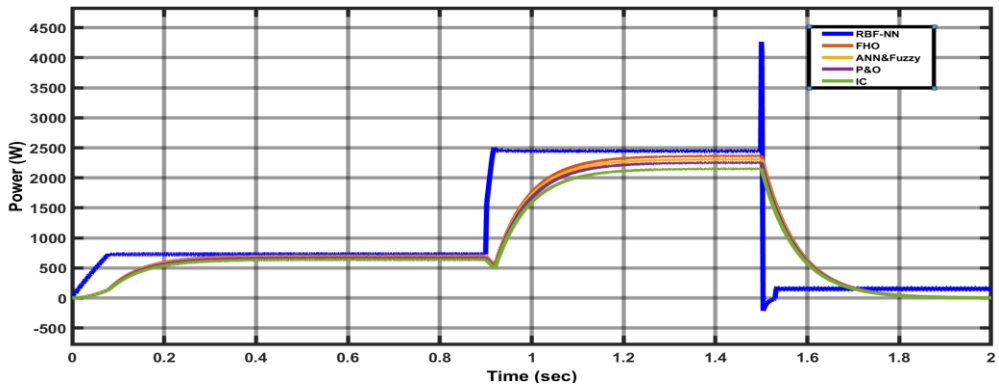


Figure 6: Output power comparison for RBF-NN algorithm in comparison with conventional algorithms

Also, the system is verified for its functionality within 24 hours of operation with all the required cases, shown in Figure 7.

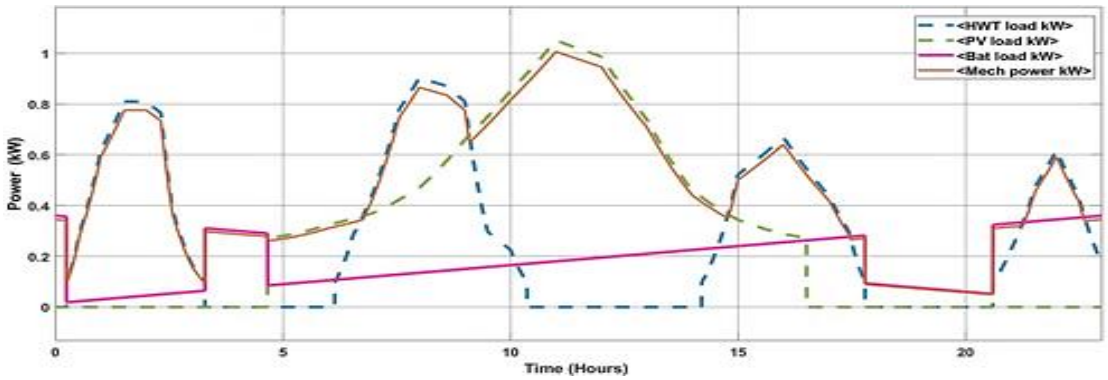


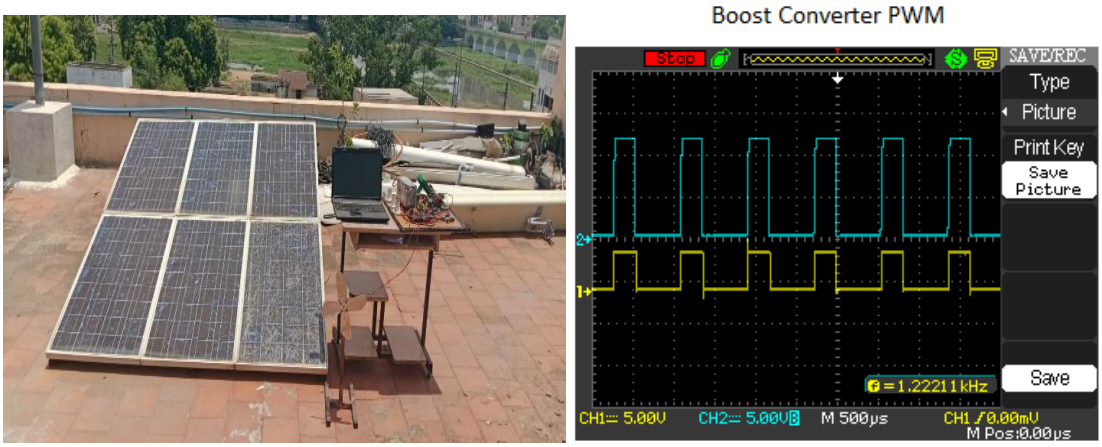
Figure 7: Simulation results for the 24-hour operation of the hybrid energy system

The performance metrics of the designed controller are verified with other algorithms, as shown in Table 1.

Table 1: MPPT algorithm comparison with conventional algorithms

Algorithm	Time Period (sec)	Power Obtained (W)	Power Tracking Efficiency (%)	Settling Time (sec)	Ripples	Accuracy for 100 count (%)	Precision for 100 count (%)	Specificity for 100 count (%)
IC	0.1 - 0.9	750	94.75	0.068	High	-	-	-
	0.9 - 1.5	2206	91.91	0.053				
	1.5 - 2	160	90.19	0.034				
P&O	0.1 - 0.9	770	96.25	0.058	High	-	-	-
	0.9 - 1.5	2297	95.7	0.038				
	1.5 - 2	167	92.77	0.051				
ANN with Fuzzy	0.1 - 0.9	780	97.5	0.047	Negligible	93.12	96.43	94.69
	0.9 - 1.5	2357	98.2	**0.021**				
	1.5 - 2	178	**99**	0.033				
FHO	0.1 - 0.9	776	97	0.052	Moderate	90.53	90.12	92.56
	0.9 - 1.5	2414	98.53	0.029				
	1.5 - 2	173	97	0.045				
RBF-NN	0.1 - 0.9	800	**99.79**	**0.034**	Negligible	99.76	99.33	99.63
	0.9 - 1.5	2450	**98.87**	**0.021**				
	1.5 - 2	180	**99.28**	**0.018**				

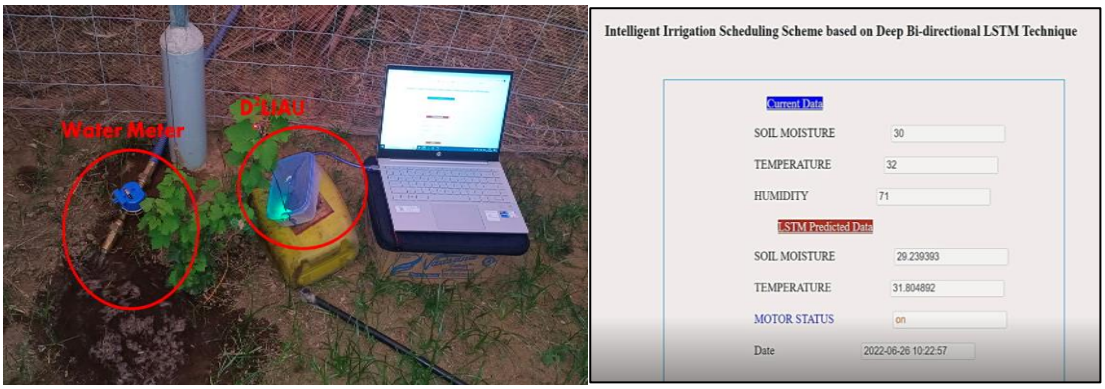
The federated deep learning algorithm has been considered for real-time implementation. The same was developed with a hardware prototype with a solar and wind turbine interconnected, as shown in Figure 8.



(a) **(b)**

Figure 8: (a) Hardware implementation of the hybrid energy system with federated deep learning algorithm (b) PWM signal obtained from the boost converter

The hardware circuit anonymously performed well for the designed algorithm without any issues by training on its own for all variations. Then, the final thing is the implementation of the field experimentation carried out for the grape plant at the mentioned location in Tamil Nadu with the development of the Deep Data Logger and Irrigation Activator Unit. The roots of the grape plant may reach up to 10 to 40cm, so the soil moisture is placed at a distance of 30 cm, as shown in Figure 9.



(a) **(b)**

Figure 9: (a) Real-time verification of Deep Data Logger and Irrigation Activator Unit in a farm (b) Remote monitoring of the farm's condition and prediction

The data logging unit fetches the farm's information, and the corresponding ET_0 value is found. Simultaneously, the deep learning unit after capturing the monitored values of the irrigation activation unit, predicted the future climatic conditions and estimated the amount of water required for irrigation. The measured data reveals that the irrigation based on the developed device consumes less amount of water when

compared with the manual irrigation process. It was found that the device achieved nearly 63 to 75 % less water consumption when compared with manual irrigation.

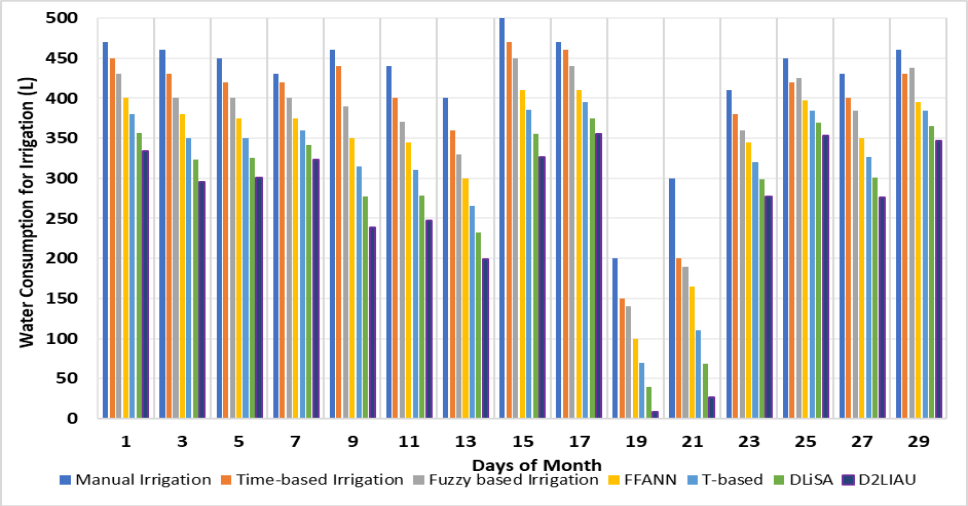


Figure 10: Irrigation water consumption comparison with all algorithms

7. ORGANIZATION OF THE THESIS

The structure of this thesis is organized into eight chapters, as follows:

Chapter 1

This chapter describes the motivation behind using renewable energy sources and their effectiveness. It also explains the importance of using renewable energy sources for farming in precision agriculture.

Chapter 2

A review of the works carried out by researchers with various MPPT algorithms for renewable energy systems and precision agriculture technologies with wireless sensor networks has been reported in this chapter. The motivation behind the proposed methodology has also been defined here.

Chapter 3

This chapter discusses the conventional methods of MPPT algorithms, such as the P&O and fuzzy logic algorithms. Also, it states the methodology utilized as a single Artificial neural algorithm controller to overcome the shortfalls the conventional algorithms meet. It also briefly compares the neural algorithm with a traditional algorithm regarding maximum power tracking, settling time and efficiency obtained during simulation analysis with MATLAB Simulink environment.

Chapter 4

This chapter encapsulates the design and analysis of a hybrid master power controller with a Radial Basis Function Neural Network (RBFNN) algorithm to overcome the issues faced by the artificial neural algorithm with MATLAB Simulink environment. Along with the comparison with conventional algorithms, it showcases the operation of the controller for 24 hours of operation.

Chapter 5

This chapter elaborates on the deep learning-based controller for hybrid renewable energy sources. The federated deep learning control strategy is considered in this work. The hardware implementation is done with Arduino, proteus design suite and Python for programming. The prototype functioning has been verified with a small miniature structure. The outputs are compared for their efficiency with other algorithms.

Chapter 6

This chapter deals with the application implementation of the designed controller. The considered application is irrigation prediction and estimation with the Deep Bi-directional Long Short-Term Memory (DBLSTM) technique. The controller is developed with Arduino, integrated with the LSTM algorithm, and verified on a grape plant on a farm for 30 days. The algorithm is compared for its functionality and compared with other irrigation methods.

Chapter 7

This chapter draws a conclusion to the thesis and discusses the future work to be carried out in this context.

8. CONCLUSION

The maximum power point tracking efficiently operates the renewable energy sources by effectively tracking the voltage and current of the energy sources according to the battery voltage and the load demand. The major problem in identifying the MPPT is that the DC link voltage is unstable due to the integration of hybrid renewable energy sources. To meet the shortfalls faced by hybridizing renewable energy sources, a single master controller was designed. Initially, a single

controller was designed with conventional algorithms P&O and fuzzy logic algorithm. The design was simple and easy to prepare, but it failed to meet the MPPT accurately, and the MPP oscillated. So, a basic artificial intelligence-based MPPT controller is designed using MATLAB Simulink environment. The system was trained with a Whisper 200 - 1kW PMSG turbine data and 1.65kW capacity solar panels installed at the National Institute of Wind Energy campus in Chennai to implement the AI algorithm. The interpretation obtained by the adopted control strategy is that it performs faster in settling time at 0.018 seconds with negligible ripples. Also, the system is accurate, precise and efficient compared to other algorithms. While carrying out the preliminary setting of neurons and basic functions is a bit tough to find out, it is very sensitive to data dimensionality. Though the training is faster, the classification is slow in the RBF-NN algorithm.

To address the classification issues faced by the RBF-NN algorithm, the next algorithm considered is Federated Deep Control (FDC), which is operated with a multi-tasking approach where individual learning progress is carried out for every instance and global variants are generated for its efficient achievement of the problems. The same was implemented in a real-time environment for its operation. The obtained results were satisfactory and can be considered for development. Then comes the final application part, where the agricultural farm monitoring and prediction of irrigation period and volume was carried out. A Deep Bi-directional Long Short-Term Memory has been proposed for irrigation activation from a remote location with a Deep Data Logger and Irrigation Activator Unit (D^2LIAU). The developed device with the proposed algorithm has been designed in an Anaconda Python compiler and validated with a prototype model. The data for the entire 2020 and 2021 are taken for the farm location from the NASA website for training the system. The training metrics achieved gave RMSE as 0.008, MSE as 7.75e-^{05}, and NRMSE as 0.012. Also, the Deep Bi-directional Long Short-Term Memory has higher reliability, consumes less water in a shorter period, and reduces water consumption. All these systems are combined to form a compact solution for the future generation of less renewable energy-based irrigation practices.

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